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Identification and quantification of drivers of forest degradation in tropical dry forests: a case study in Western Mexico

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Abstract

The intensity of forest degradation is linked to landowners´ decisions on management of their shifting cultivation systems. Understanding the processes involved in this land use type is therefore essential for the design of sustainable forest management practices. However, knowledge of the processes and patterns of forest transition that result from this practice is extremely limited. In this study we used spatially-explicit binary logistic regression to study the proximate factors that relate to forest degradation by combining biophysical and socio-economic variables. Our study region is within the Ayuquila Basin, in Western Mexico, a typical fragmented tropical dry forest landscape dominated by shifting cultivation. Through a survey and semi-structured interviews with community leaders we obtained data on the forest resources and on the uses that people make of them. Detailed forest cover maps for 2004 and 2010 were produced from high-resolution SPOT 5 data, and ancillary geographical data were used to extract spatial variables. The degree of social marginalization of each community and the ratio of forest area to population size were the main factors positively correlated with the probability of the occurrence of forest degradation. Livestock management and use of fence posts by the communities were also positively associated with forest degradation. Among biophysical factors, forest degradation is more likely to occur in flatter areas. We conclude that local drivers of forest degradation include both socioeconomic and physical variables and that both of these factors need to be addressed at the landscape level while developing measures for activities related to REDD+.

Keywords**:** forest degradation, drivers, shifting cultivation, logistic regression, *ejido*, tropical dry forests, REDD+, forest cover change

1. Introduction

Determining the proximate and underlying causes of deforestation and forest degradation of tropical forests is a key prerequisite for the development of activities for REDD+ (Reducing Emissions from Deforestation and Forest Degradation) (Salvini *et al.*, 2014). Developing countries participating in REDD+ are encouraged to report on human-induced activities that are linked to greenhouse gas (GHG) emissions from forest land (UNFCCC, 2010; Hosonuma *et al.*, 2012). The identification of these activities and locating them in a spatially explicit manner may be of utmost importance for effective REDD+ interventions (Kissinger *et al.*, 2012). While there is considerable understanding of the processes causing deforestation (Geist & Lambin, 2002), knowledge of drivers that cause changes in forest carbon stocks in forests that remain forests (i.e. degradation) is quite limited, especially for tropical dry forests (TDFs) (Murdiyarso *et al.*, 2007).

Tropical dry forests have not received as much attention as humid forests in the context of REDD+, mainly because they have lower carbon stocks and increments per area (Blackie *et al.*, 2014). Nonetheless, TDFs cover extensive areas (approx. 42% of the tropics and subtropics worldwide (Murphy & Lugo, 1986; Miles *et al.*, 2006)), and may potentially play an important role in climate change mitigation. They are notably important ecosystem in the Neotropics, where they cover an area of approx. 520,000 km^2 (Portillo-Quintero & Sánchez-Azofeifa, 2010), that corresponds to more than half of the global total extent of TDFs (Miles *et al.*, 2006). Moreover, TDFs provide a variety of ecosystem services (Maass & Balvanera, 2005) and although holding lower values of species richness than rainforests, they have particularly high levels of endemism and beta biodiversity (Gentry, 1995).

Despite their importance in providing ecosystem services, TDFs are among the most threatened ecosystems in the Neotropics (Miles *et al.*, 2006). They have suffered high conversion rates and the remaining areas are heavily degraded and fragmented (Trejo & Dirzo, 2000; Sánchez-Azofeifa *et al.*, 2005). This is because TDFs often support high human population densities, with many people depending on forest land and forest resources (hereafter forest resources) for their livelihoods (Sunderlin *et al.*, 2008); particularly through shifting cultivation (Saikia, 2014), but also to provide fuelwood, charcoal, house-building materials, fence posts and non-timber forest products (NTFP) (Maass & Balvanera, 2005). In addition, commercial logging and cattle grazing frequently affect the structure and composition of TDFs (Sanchez-Azofeifa & Portillo-Quintero, 2011).

This paper presents an analytical framework to identify drivers of forest degradation in TDFs and other variables that are correlated with it. Satellite imagery that provides data at a scale fine enough to detect forest degradation due to shifting cultivation is used together with on-the-ground data on the local use of forest resources. It is important to stress that, in our analysis, shifting cultivation (here meaning slash-and-burn agriculture, subsistence farming and swidden cultivation, following the terminology of Mertz (2009)) is considered to cause forest degradation rather than deforestation because its cycle of operation involves clearance followed by regrowth of forest that creates a landscape with lower biomass density that still qualifies as forests, in contrast to deforestation that implies a permanent conversion of land cover from forest to non-forest (Houghton, 2012). As a result, landscapes where shifting cultivation is practiced are complex mosaics made up of patches that are losing or gaining forest carbon stocks (Mertz *et al.*, 2012). However, although there can be carbon gains at the landscape level during particular periods of time, in their early development stages the resulting secondary forests on average usually hold lower carbon stocks than mature forests (Read & Lawrence, 2003; Lawrence *et al.*, 2005; Becknell *et al.*, 2012). Furthermore, lower capacity to store carbon and modified species composition have been observed in secondary forests as an area is subject to more cycles of clearance and recovery (Lawrence *et al.*, 2010). Therefore, they must be considered as degraded forests in the REDD+ context, both in terms of carbon stocks and regarding their ecological characteristics. However, since most of the discussion on forest degradation have been on selective logging (Putz & Redford, 2010); the inclusion of shifting cultivation as a driver of forest degradation within REDD+ is unclear, and this has significant consequences on countries carbon stock estimations (Pelletier *et al.*, 2011). The core questions relies on whether fallows are classified or not as forest land; while the IPCC (Penman *et al.*, 2003) considered fallows as land under predominantly agricultural use, in reality it is a stage of forest re-growth. Most importantly, the methods used by most countries do not distinguish secondary growth due to shifting cultivation from other types of secondary forest (Houghton 2012). Consequently, we argue that these stage of secondary re-growth should be considered degraded forest, because it is not a permanent loss of forest cover to be classify as deforestation and it holds less carbon density.

In order to capture the pattern of forest clearance and subsequent regrowth of forests carbon stocks, observations and analysis at suitably fine spatial and temporal scales are required. Previous studies which analyzed multiple dates are limited by coarse and medium spatial resolution (Li *et al.*, 2014) and may not be adequate to detect patches of small-area agriculture ($\pm$2 ha) with short cycles of forest clearance and regrowth (3-6 years). Many studies have used spatial scales that are too coarse to detect degradation related to shifting cultivation, e.g. Bonilla-Moheno *et al.*, (2013) used data from

MODIS with a pixel size of around 250 m. Multi-date medium resolution Landsat data (30 m) have been used in combination with detailed field inventories to detect shifting cultivation in rainforests where clearings are on average ± 2 ha (Pelletier *et al.*, 2012). Clearings and fallows were classified using spectral unmixing analysis, a technique that has been successfully applied to the detection of selective logging mostly in moist and wet tropical forests (Asner *et al.*, 2005; Souza *et al.*, 2005). However, in TDF coarser spatial and temporal resolution limits the capacity to differentiate between natural open forest areas that have never been cleared and degraded forest or forest recovering after clearance via secondary regrowth, because of overlapping spectral signatures. So far, to the best of our knowledge, only one study (Hurni *et al.*, 2013) has managed to delineate landscape units in which shifting cultivation prevails, by using higher spatial resolution (10 m pixel) satellite data. Nonetheless, this analysis was only done for a single date, i.e. it does not examine change over time.

The scale of analysis is also extremely important in evaluating the human factors that could potentially influence the observed patterns of forest degradation defined by cycles of regrowth and clearance. Typically, proximate causes of forest cover change are hypothesized and tested from national census datasets or data that are aggregated at regional or municipal level because they are readily available. As a result, these analyses may be of limited utility in evaluating local processes in dynamic socio-ecological systems such as shifting cultivation landscapes (Geoghegan *et al.*, 2004). Only a few studies (e.g. Roy Chowdhury, 2006; Getahun *et al.*, 2013) have integrated community-level information or analyzed it across scales from household to regional (e.g. Overmars and Verburg 2005). Likewise, regional studies that evaluate factors that affect forest degradation at a landscape level are rare (Saikia, 2014).

This situation is not desirable in the context of REDD+ because on-the-ground projects are implemented at a landscape level, and activities are undertaken by individuals and communities on their own parcels of land. To tackle efficiently the causes and consequences of forest degradation, analysis at a scale compatible with the degradation processes is needed. For example, in Mexico, where some studies have claimed that as much as 80% of the forest area is on communal land managed by rural agrarian communities (Bray *et al.*, 2006), data at the community level is required (Skutsch *et al.*, 2013). These agrarian communities are in any case the target group of most REDD+ programs in Mexico (Estrada, 2010) since the policy of the Mexican government is to use REDD+ as a strategy to promote cross-sectoral rural development, as well as to foster the sustainable management of forest ecosystems (SEMARNAT, 2010).

In this paper we use as a case study a landscape in Western Mexico that contains large areas of TDF in which shifting cultivation is the traditional way of growing crops. We address three main questions: 1. Can the patterns of forest cover change in TDF be associated with forest degradation at the landscape scale? 2. Which factors determine forest degradation in a TDF landscape under a shifting cultivation system? 3. Can variation in the use of, or demand for, forest resources and forest land by communities provide an indication of the probability of forest degradation in a TDF socio-ecological landscape? To explore these questions, a detailed forest cover map was produced through an approach that allows land cover changes due to shifting cultivation to be tracked. Next, the information derived from the interpretation of this map was used in a statistical model that allows the identification and quantification of the probability of forest degradation from an integrated set of biophysical and socio-economic variables. Finally, we further explore the relationship between the use of forest resources such as firewood and poles, and forest degradation associated with shifting cultivation, to explore the utility of using demand for forest resources as an indicator for monitoring forest degradation in the context of REDD+.

2. Materials and Methods

2.1 Study Site

The study was carried out in the Ayuquila Watershed (~19°25' - 20°10.0''N, 104°3' - 103°3'W), in the state of Jalisco, Mexico. The study area embraces 10 municipalities and has an area of about 4,000 km². The southern boundary of the study area is formed by the Sierra de Manantlán Biological Reserve (Fig.1), which is known for its high biodiversity and which protects a water catchment providing water for more than 400,000 people (Cuevas *et al.*, 1998). Due to its importance for water, biodiversity and other ecosystem services, and because the municipalities are already working together on environmental planning under a *Junta Intermunicipal del Rio Ayuquila* (JIRA), the area was selected as a REDD+ Early Actions Area by the Mexican government (SEMARNAT, 2010).

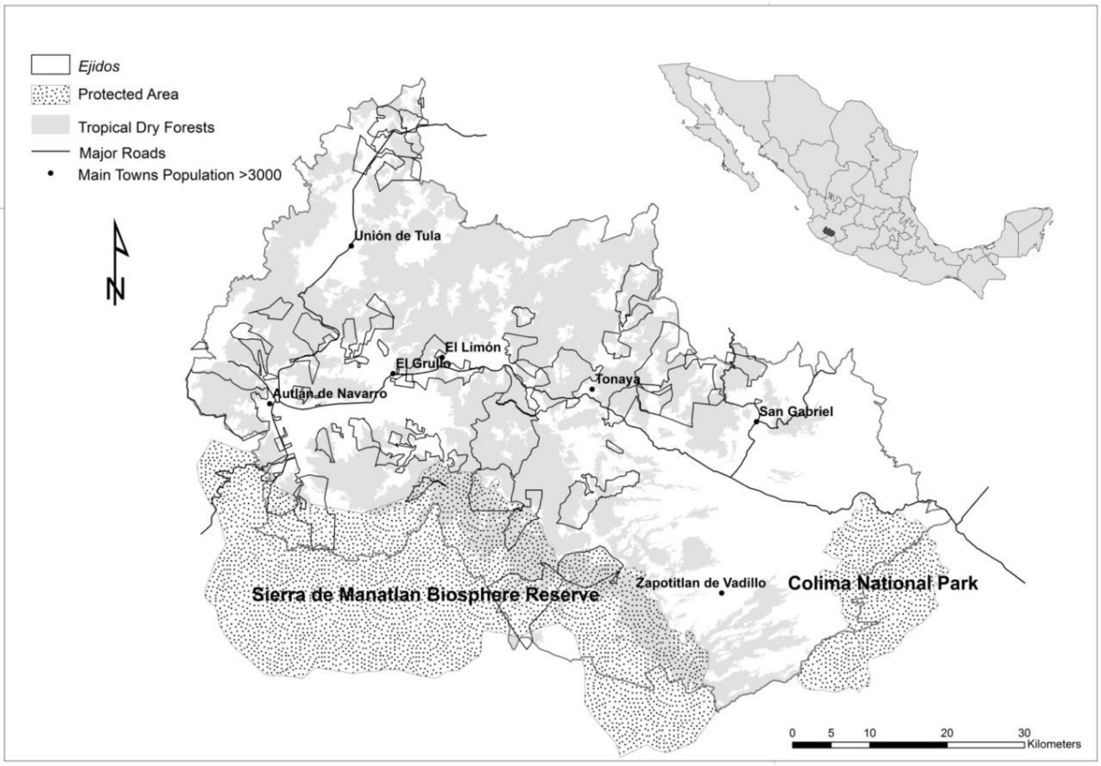

Figure 1. Regional map of the study area showing the 29 sampled communities ("*ejidos*") within Ayuquila Watershed, Jalisco, Mexico.

The study area has a complex topography that ranges from 260 m to 2500 m above sea level. The average annual precipitation is 800-1200 mm, and occurs mainly between June and October; and the range of average monthly temperatures is 18-22 °C (Cuevas *et al.*, 1998). The topographical and climatic conditions have created a variety of vegetation formations. High altitude areas are dominated by pine and oak-pine forests. At intermediate elevations, and where appropriately moist conditions are present, small patches of cloud forest are found. Lower elevations are dominated by TDF (*selva baja* (Rzedowski, 1978)). Trees in this vegetation type typically lose their leaves in the long dry season. In the undisturbed state, these deciduous and semi-deciduous forests have a height range of 4-15 m and a high number of endemic plant species (Gentry, 1995). In terms of population dynamics, the XI, and XII Population Censuses of Mexico show that the communities within the study area have not experienced major population changes in the last two decades (INEGI, 2000, 2010a).

2.2 Description of the Land Use System

The landscape is composed of a mosaic of TDF patches within a matrix of agricultural land. Most of the tropical dry forest is found within *ejidos*, which are settlements with a communal land tenure system. *Ejidos* implement a type of decentralized forest management where decisions regarding land use and management of common resources are taken in a General Assembly, which is chaired by the *ejido* leader and is composed of all those people in the community that have rights to the land (*ejidatarios*). Generally, rights to the land are established when the *ejido* is formed and can only be inherited by one person in a family. All the activities are discussed and approved in a General Assembly and, therefore, *ejido* leaders can be seen as key informants with respect to the use of resources in the *ejido*.

Land is, in principle, a communal resource. Within each *ejido*, there is an agreed division of land uses with defined areas for permanent agriculture and for shifting cultivation, as well as areas of forest. Forest is usually managed communally, although in some *ejidos* an informal privatization of this common land has occurred with each *ejidatario* managing several parcels. The main agricultural products in the *ejidos* in the study area is maize (which is either produced in the shifting cultivation system within the forested areas or in areas which have been permanently cleared for agriculture), and to a lesser extent sugar cane, avocado, and agave (all of which are planted exclusively in permanent agricultural lands).

Allocation of land use within the *ejido* is partly related to topography: permanent agriculture takes place in the low and flat areas, while hilly and stony areas are commonly used for shifting cultivation. The parcels under shifting cultivation, known as *coamiles*, have an average size of 2.5 ha and the majority of the crops are grown for subsistence (i.e. maize production is primarily for consumption within the household). *Coamiles* are typically cultivated for two-three years and then left abandoned for a fallow period that varies from three to eight years (Borrego & Skutsch, 2014). During this fallow period secondary vegetation regenerates naturally, as a mixture of shrubs and trees. When a patch of land is selected again at the start of a cultivation cycle, this secondary vegetation is cleared. Crops are then sown when the rainy season starts (June/July) and harvested six months later. Afterwards, livestock are kept on the land and fed with the crop residues before the land is abandoned to the fallow period. During the wet season, cattle move around the *ejido*, browsing on the regenerating fallows and forest lands. Consequently, there is a relationship between the number of cattle that an *ejidatario* can own and the area of shifting cultivation. In some cases, *ejidos* may only be able to support that quantity of cattle that can be maintained during the dry season fed on the crop residues of shifting cultivation areas. In addition to cattle grazing, regenerating fallows and forest areas are also the source of fence posts and fuelwood (Fig. 2).

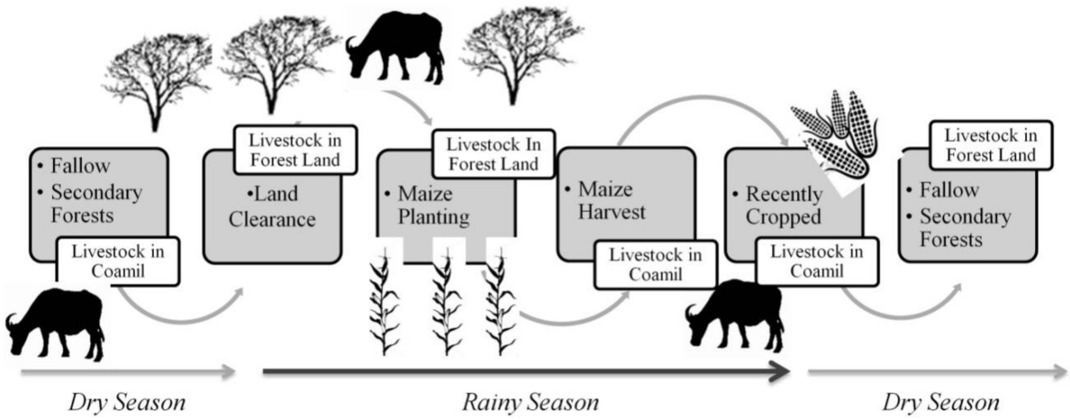

Figure 2. Illustration of the shifting cultivation system practiced within tropical dry

forests in western Mexico, based on information from field interviews. The grey boxes show a typical sequence of land cover changes in a parcel found in the area, and the white boxes show the location of the livestock.

2.3 Data

To investigate the relationship between different factors involved in forest degradation we conducted a community-level survey (described in section 2.3.2 below), together with a parallel analysis of TDF cover change. Our method to assess the probability of forest degradation uses two sets of data: 1) biophysical variables derived from remote-sensing image analysis; 2) socio-economic variables derived from the community-level survey and ancillary information. The independent variables described in Table 1 are hypothesized to be explanatory of forest cover change, which we consider to be a proxy response variable representing forest degradation in shifting cultivation landscapes. The selection of these variables was based on previous participatory mapping exercises done in five of the surveyed *ejidos* and field interviews.

2.3.1 Spatial Variables

Forest Cover Change Map as a Proxy of Forest Degradation

Temporary forest cover change was analyzed to provide an indirect measure of forest degradation. We assumed that having excluded permanent agriculture, this map reflected the temporary forest cover changes in TDF that are indicative of a shifting cultivation system with clearance and regrowth, and that this regime as a whole can represents a form of forest degradation.

This forest cover map was based on SPOT5 imagery for the years 2004 and 2010. The study area was covered by four scenes corresponding to the dry season (Table S1), when there is the best discriminatory capacity for change detection in dry forests (Kalacska *et al.*, 2008). The images were atmospherically and geometrically corrected to facilitate detection of change over time. Atmospheric correction was performed using FLAASH as implemented in Envi 4.7 (Exelis Visual Information Solutions). The geometric correction achieved an accuracy of less than one pixel (10 x 10 m) and images were re-sampled using the nearest neighbour method. Images were mosaicked and co-registered to obtain a pixel-to-pixel correspondence between the two dates (Table S1).

The classification of tropical dry forests and shifting cultivation landscapes is a difficult task, because of the overlapping spectral signature that these land covers have as well as the temporal dimension. Therefore, a previous step was to mask out land cover types not of interest for this study, mainly permanent agriculture and vegetation types different from TDF. This mask was created by segmenting the 2010 image (criteria minimum region size of 1500 pixels, using the mean shift segmentation algorithm). Firstly, segments that match what was classified as permanent crop, urban, bare, permanent pasture, or pine and oak forest land according to maps produced by the National Institute for Geography and Statistics (1:250,000) (INEGI, 2010b) were excluded. This allowed us to remove the bulk of the permanent agricultural areas. Then, any segments found above 1500 m.a.s.l. were removed, because they are outside the distribution range of TDF in the study area. To further refine the mask, we used image visual interpretation in combination with random field GPS points and ancillary data. Segments were checked against Google Earth historical images (2000-2012), and if the segment had no visible vegetation over that period it was excluded. Segments were differentiated based on their spatial context: permanent agriculture usually covers large continuous areas of flat land (<10° slope) that is usually planted with agave, sugar cane or maize; whereas shifting cultivation is carried out on hilly areas and on smaller parcels that are embedded in forest vegetation. The visual interpretation of the images was ground-truthed during one year of fieldwork in 2011-12.

The final mask was applied to the 2004 and 2010 images. Masked images were classified using the Random Forests algorithm (Liaw & Wiener, 2002; Horning, 2012), because of its outstanding performance (Rodriguez-Galiano *et al.*, 2012; Mellor *et al.*, 2013). For the image classification, the following vegetation and textural indices were calculated: a) Homogeneity index of band 2 and 3 using a 3 X 3 pixel moving window; b) Normalized Vegetation Index (NDVI), c) Canopy Index (CI) and d) Soil Modified Adjusted Index (SAVI) (Table S2). The final images used as input for the Random Forests model consisted of the four SPOT5 bands, three spectral indices (NDVI, CI, SAVI) and the homogeneity index for band 2 and band 3. The selected spectral indices, mainly NDVI and SAVI, are widely used to enhance the contrast between soil and vegetation, while CI which includes the short wave infrared band (SWIR) has been shown to be suitable for estimating vegetation biophysical characteristics especially above-ground biomass (Eckert & Engesser, 2013). The use of the homogeneity index based on the Red and Near Infrared Band has proved useful for estimating successional stages in TDF (Gallardo-Cruz *et al.*, 2012), and was therefore used in our analysis. Each image was classified into three classes: tropical dry forests (>10% crown cover); shifting cultivation (<10% crown cover), i.e. land that was actively being used for the cultivation phase; and others (shadows and clouds). Training samples were selected on each of the classes based on 243 random GPS field points acquired during field work during 2011-2012.The classified images from 2010 were validated with 94 randomly selected field points. All the image classification and validation procedures were carried out using a combination of Qgis 2.2 (QGIS Development Team, 2012) and R 3.0.0 (R Core Team, 2013).

Finally, the area of regrowth and clearance of TDF was estimated for the whole landscape and for each community. The information derived from this map was used to extract the response variable used in the statistical model.

Other Biophysical Variables

Other potential explanatory variables were derived from ancillary data, namely altitude, slope, distance to the closest major town (population > 3000) and distance to the nearest road. These variables were selected because they have been used in the identification of factors associated with vegetation changes in previous studies (Crk *et al.*, 2009). Both altitude and slope were derived from a 30 X 30 m resolution digital elevation model (CEM 2.0 from INEGI) and slope percentage was mapped using a 3 X 3 pixel moving window. The distance to the nearest main town was calculated for each point using the tool Hubdistance, available in Qgis 2.2 This tool iterates until it finds the shortest ellipsoidal distance to the closest hub (a town in this case) from a defined point (see sampling procedure in the next section). The distance to the nearest road was calculated as the perpendicular distance between a defined sampling point and the road, this was done using the Near Tool in ArcMap10.0.

2.3.2 Socio-economic variables

The socio-economic data were acquired through a survey carried out in 2012 in 29 *ejidos* of the Ayuquila basin (Fig. 1). The selected *ejidos* were those with ≥ 20% TDF cover as reported in the INEGI IV Vegetation Map (INEGI, 2010b); their mean TDF cover was 43.6% (± S.D. 18%). The boundary of the land area of each *ejido* was obtained from the National Rural Agrarian Registry (RAN).

Socio-economic variables were obtained by household surveys and semi-structured interviews. The survey was informed by previous fieldwork in the area that included participatory mapping in five communities and informal interviews with community leaders. This previous work provided information on how the population of the *ejidos* used their forest land and what resources were obtained from this forest that could potentially be associated with forest degradation. A detailed description of how the survey was designed and applied is provided in Borrego & Skutsch (2014). Over the 29 *ejidos*, the survey of 300 households provided data from which a number variables could be calculated at *ejido* level, namely parcel size cultivated per year, total number of livestock, fuelwood loads and number of fence posts used per year (Table 1). The semi-structured interviews with the *ejido* leaders included questions on management practices, main economic activities and the farming system. Information on the population size and marginalization index of each *ejido* was derived from the national Census of Households and Population 2010 (CONAPO, 2012). Marginalization index variables were used as dummy variables (Table 1).

Table 1. Description of the explanatory variables tested in the statistical model for prediction of forest degradation (bold letters indicate the variables included in the final model).

Variable	Description (Unit)	Mean	S.D.	Spatial Unit
Elevation[1]	Metres above sea level (masl)	1163.4	261.5	Pixel
Slope[1]	Slope percentage (%)	35.2	18.0	Pixel
Slope_Elev[1]	Slope*Elevation (interaction variable)	42959.2	27363.1	Pixel

Dist[2]	Topographic distance to nearest main town (km)	10.6	4.9	Pixel
Road[3]	Topographic distance to nearest road (m)	947.8	721.7	Pixel
Livestock[4]	Number of cows	1991.8	1743.7	*Ejido*
Fence[4]	Number of posts harvested per year (a post length is about 1.5 m)	1467.2	1032.1	*Ejido*
Fuel[4]	Average number of fuelwood loads harvested (a load comprises ca. 50-60 small branches)	392.0	408.7	*Ejido*
Parcel_S[4]	Average parcel size cultivated (ha)	6.2	2.9	*Ejido*
Ejidatarios[4]	Number of registered farmers with land rights	107	97.8	*Ejido*
Parcel_T[4]	Number ejidatarios x parcel size (interaction variable, proxy for total cultivated land)	836.9	775.2	*Ejido*
TDF:Pop[5&6]	Ratio between total TDF area and the total population in the ejido	9.6	14.2	*Ejido*
MMI[6]	Medium Marginalization Index: an indicator based on income, education, housing, and population density	9.7	2.1	*Ejido*
HMI[6]	High Marginalization Index: an indicator based on income, education, housing, and population density	6.8	0.4	*Ejido*

Data Sources: 1 = CEM-DEM- Instituto Nacional Estadística y Geografía (INEGI) (30 X 30 m), 2 = Population map from Instituto Nacional Estadística y Geografía (INEGI) (1:50,000); 3= Road Network from INEGI (1:50 000));4 = Questionnaire survey (this study); 5 = Land Use and Vegetation Map (2010) from INEGI (1:250 000); 6 = Household census (CONAPO 2010).

2.4 Sampling procedure for analyses

A total of 2000 random points were established within the 29 selected *ejidos* to derive both dependent and explanatory variables for the statistical model. The number of sampling points selected for each *ejido* was proportional to its estimated TDF area according to the INEGI Vegetation Map (INEGI, 2010b). We used a random sampling procedure (so that the distance between neighboring pairs of points varies) and evaluated spatial autocorrelation of the dependent variable in our statistical model using three tests: Moran *I*, a geographical representation of model residuals and a semi-variogram of model residuals. To test if there was any spatial autocorrelation, these tests were run for both the random grid and for a set of 2000 points selected randomly from a 300 m X 300 m grid. No difference in the value of the three tests was found, therefore the random points data set was used for the remaining analyses. Sampling points that fall in areas with cloud cover were eliminated from the analysis, therefore the model was developed using 1952 points. Sampling points were selected using the Research Analysis Tool available in Qgis 2.2 and spatial autocorrelation was analyzed using the ape (Paradis *et al.*, 2004), gstat (Pebesma, 2004) and sp (Pebesma & Bivand, 2005) packages in R 3.0.0.

2.5 Data analyses

For each of the 1952 sample points the environmental/socio-economic variables described in Table 1 and the response variable were extracted to model the probability of forest degradation in TDF. The probability that a pixel will be degraded depends on choices made by the *ejidatarios* within a decision context (e.g. farmers' preferences, economic returns etc.) so the dependent variable can be considered an unobserved variable y_i^* corresponding to the observed outcomes, in this case TDF cover change per pixel, that do not directly reveal information on farmers' preferences or economic returns. Consequently in this analysis there are two possible outcomes: a) forest degradation (coded as 1), i.e. there has been a change between cover classes from TDF to shifting cultivation (or vice versa) and b) no change in cover class (coded as 0). As was explained in the introduction section above, due to the complex mosaic landscape of the study area we considered any change in a pixel, both TDF cover clearance and regrowth, as an indicator of forest degradation. The outcome is a discrete dependent variable measured on a nominal scale. Statistically, the output corresponds to a binary model in which the unit of observation is a pixel y^* and is assumed to be a linear function of a set of explanatory variables as follows:

$$y_i^* = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_n x_n + \varepsilon \qquad (1)$$

where y_i^* is the probability of a pixel being degraded; β_0 is the intercept capturing features that do not depend on a given pixel's characteristics; $\beta_1, \beta_2, ...\beta_n$ represent coefficients estimated through regression analysis; $x_1, x_2, ...x_n$ are explanatory variables; and ε is the residual error.

If we assume that the residuals have a logistic distribution the probability of forest degradation $\{Y = 1\}$ can be written as:

$$P\{Y = 1\} = \frac{e^{\beta_0 + \beta_1 x_1 + \beta_2 x_2 ... \beta_n x_n}}{1 + e^{\beta_0 + \beta_1 x_1 + \beta_2 x_2 .. + \beta_n x_n}} \qquad (2)$$

and the model can be estimated with the maximum likelihood approach (Menard, 2010).

The use of logistic regression to model probability of land cover changes is a well-established technique (Overmars & Verburg, 2005; Roy Chowdhury, 2006). The magnitude and direction of $\beta_1, \beta_2, ...\beta_n$ indicate the importance and effect of each factor in the probability of forest degradation.

One potential source of error in logistic regression analysis is collinearity of variables. We tested for correlation between independent variables (Table S3), and in cases where correlations > 0.8 were detected between a pair of variables, only the variable with the strongest impact on the model was retained, as recommended by (Menard, 2010).

Models were evaluated by tests of goodness of fit by using log-likelihood, based on deviance residuals of the null and fitted models and the Akaike Information Criteria (AIC) to compare between models and select the final one. Prediction accuracy of the model was evaluated by estimating the area under the receiver's operational curve (AUC-ROC) using an independent dataset (Pontius & Schneider, 2001). The magnitude of the effect of each variable on the probability of forest degradation was estimated using marginal effects based on the mean values of each variable. Finally, we evaluated the relative importance of each of the variables in the final model by comparing the difference in the values of log-likelihood. All the statistical analyses were performed in R 3.0.0., using the ROCR package for ROC analysis.

Pearson correlation analysis was used to explore how the variation in the use/demand of forest resources by the *ejidos* (i.e. input variables for the model) related to the change in TDF cover. This analysis was done to further evaluate if a higher intensity of demand for forest resources is linked with regrowth or clearance of TDF cover and therefore whether these variables can be used as a practical indicator in this context.

3. Results

3.1 Patterns of regrowth and clearance for the tropical dry forest cover

Approximately 65% of the study area showed no change in TDF cover between 2004 and 2010, and was therefore presumed not to have been used for shifting cultivation at all. About 35% of the study area (which was made up of 20 936 ha of TDF clearance, 24 090 ha of regrowth, and the areas under shifting cultivation (Table 3)) can be considered as degraded TDF. From this, 24% underwent transition (cover clearance or gain) (Fig 3 & Table 2), indicating that it had been used for shifting cultivation between these dates but was not being cultivated in these particular years and 11% was classified as under the cultivation phase of shifting cultivation in both dates (Table 3). The areas classified as shifting cultivation on both dates (i.e 11% of the study area), most probably were cultivated in 2004, then left to rest and started a new cultivation cycle shortly before 2010. As the area of clearance and gain of forest cover is similar (Table 3), forest cover in the region may be considered stable in the long run, despite the fact that at least 24% of the area was undergoing cover change. This highly dynamic pattern of TDF cover is replicated in most of the 29 individual *ejido:* with 17 experiencing a transition in TDF cover on more than 20% of their area, a further six on 15-20% of their area, but none experiencing a net loss of TDF cover of more than 15% of their total area, and only four having a net loss between 10 and 15% (Table S4).

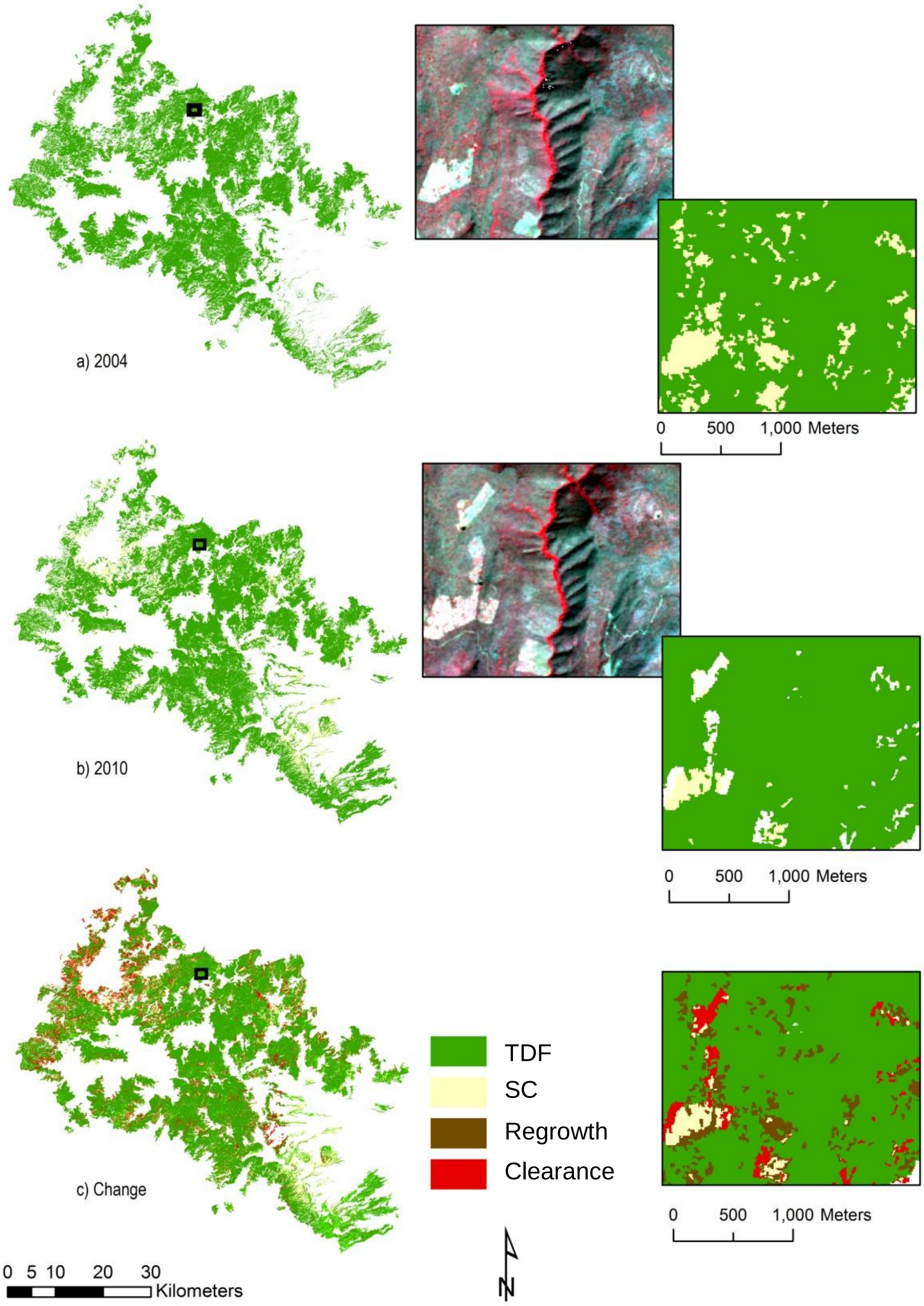

Figure 3. Tropical dry forest (TDF) and shifting cultivation (SC) land cover in the Ayuquila Basin, Jalisco, Mexico. a) TDF and shifting cultivation cover in 2004, b) TDF and shifting cultivation cover in 2010, c) Change in cover between TDF and shifting

cultivation 2004-2010. Overall accuracy for 2010 = 98%, kappa coefficient equals 0.973, Minimum mapping Unit (MMU) = 0.9 ha (3 X 3 pixels) .

Table 2. Estimated areas of tropical dry forest (TDF) and shifting cultivation cover for 2004 and 2010 in the Ayuquila Basin, Jalisco, Mexico.

Land Cover Type	**2004 (Ha)**	**2010 (Ha)**
TDF	140 836	143 990
Shifting cultivation	44 583	41 429

Table 3. Area estimated for each transition between land cover types in the Ayuquila Basin, Jalisco, Mexico.

Transition 2004-2010	**Area (Ha)**	**%**
No change, TDF	119 901	64.7
No change, shifting cultivation	20 493	11.1
Change, shifting cultivation to TDF (forest regrowth)	24 090	13.0
Change TDF to shifting cultivation (forest clearance)	20 936	11.3

3.2 Factors influencing and related to forest degradation

Alternative models using socioeconomic and biophysical data for the 29 *ejidos* as explanatory variables for the probability of TDF degradation were developed. The variables livestock and fuelwood were highly correlated (r= 0.81, p <0.001) (Table S3), therefore only livestock number was used for model development. We selected the model that had the highest log-likelihood ratio and lowest AIC and residual deviance.

The selected model included eight variables, plus an interaction term between slope and elevation (Table 4). The evaluation of model residuals showed a slightly positive spatial autocorrelation (Moran's I = 0.015, p <0.001). However, as the model residuals and semi-variogram revealed no spatial structure (Fig. S1 & Fig. S2), no further adjustment of the model was made to account for spatial structure, as the use of spatial autoregressive models is not recommended for logistic regression (Dormann, 2007).

Both biophysical and socioeconomic variables were significantly associated with the probability of TDF degradation (Table 4). The model results indicated that for every 1% increase in slope there is a decrease of 0.84% in the probability of forest degradation and that slope is the most important biophysical factor for determining if an area will be used for shifting cultivation. In the case of distance from a parcel of land to nearest main town, for every increase of one kilometer, there is a decrease in the probability of forest degradation of almost 0.5%. There is interaction between slope and elevation; although probability of forest degradation decreases with slope, it increases at higher elevations with small slopes angles, which may be linked to the use of flat areas on hilltops for shifting cultivation which is common in our study area. Of the socioeconomic variables, the one with the strongest relationship to the probability of forest degradation was found to be “high degree of marginalization” of the community. Comparison of the relative size of the marginalization index variables, showed that both highly marginalized communities and medium marginalized communities have a greater probability of forest degradation (12.3% and 8.4% respectively) than communities with a low index of marginalization. The model showed that a higher ratio of TDF to population size decreased the probability of degradation; this means that the more TDF that is available person, the lower the pressure will be on TDF (Table 4). The results also revealed that the number of fence posts used per year and the number of livestock were both positively correlated with the likelihood of forest degradation. The value of the livestock and fence coefficients (0.002% and 0.005%) indicate the marginal impact of one unit change in these variables.

Variables were ranked according to their importance (i.e. their contribution to the log-likelihood value of the model estimation). The relative effect showed that the biophysical variables, which were observed at pixel level, contributed altogether to 39% of the log-likelihood value of TDF degradation, and community-level information explained around 61% (Table 5). Among the biophysical variables Slope and Slope_Elev combined explained 34 % of the variance of the model; while among the socio-economic variables, the number of fence posts ranked highest, accounting for 21% of the log-likelihood value, followed by the high marginalization index (17%).

Table 4. Model results and estimated probability of occurrence of TDF degradation as a function of a series of potentially explanatory variables in the Ayuquila Basin, Jalisco, Mexico (for variable names see Table 1).

Variable Name	**Estimated coefficient (*b*)**	**S.E.**	***p***	**Marginal effect**
Slope	-0.06121	0.01119	0.0000	-0.8424
Dist	-0.03539	0.0161	0.0281	-0.4870
Road	-0.00036	0.0001	0.0010	-0.0050
TDF:Pop	-0.01778	0.0067	0.0075	-0.2447
Fence	0.00033	0.0001	0.0001	0.0046
Livestock	0.00017	0.0001	0.0032	0.0024
HMI	0.89220	0.2189	0.0000	12.2787
MMI	0.61050	0.2498	0.0145	8.4019
Parcel_T	-0.000415	0.0002	0.0180	-0.0057

Slope_Elev	0.00004	0.00001	0.0000	0.0005
Constant	-1.38800	0.3052	0.0000	-19.1020

n = 1952, S.E. = standard error of estimation of the model, model log likelihood ratio = -763.76 (df = 11); AUC = 66.35; residual deviance = 1527.5; null deviance = 1605.2;AIC = 1549.5

Table 5. Contribution of explanatory power for each variable in the statistical model in the Ayuquila Basin, Jalisco, Mexico (for variable names see Table 1).

Variables	**Change in Log Likelihood (*df*)**	**% Explained by each Variable**	**Variable Importance Rank**
Intercept	-802.6		
Slope + Slope_Elev	-789.3 (3)	34.1	1
Fence	-768.9 (9)	20.8	2
HMI	-780.8 (6)	17.1	3
Parcel_T	-763.7 (11)	7.6	4
TDF:Pop	-777.0 (8)	7.0	5
Livestock	-766.71 (10)	5.7	6
Dist	-788.0 (4)	3.2	7
MMI	-779.7(7)	2.8	8
Road	-787.47 (5)	1.6	9
Total		100	

The model's goodness of fit (AUC = area under the curve) was 0.66 (Fig. 4), which means that it can correctly predict changes from TDF to shifting cultivation and *vice versa* with a probability of 0.66, which is better than that predicted only by chance (AUC =0.5) (Gellrich *et al.*, 2007).

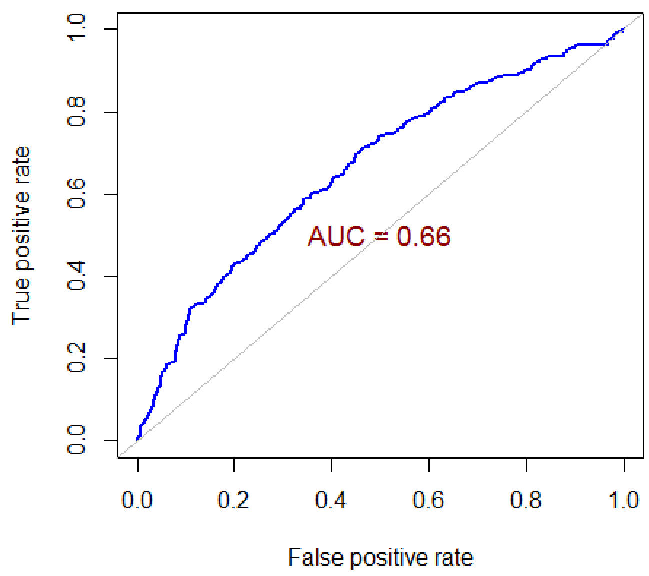

Figure 4. Receivers operating characteristic (ROC) curve for the probability of TDF degradation in the Ayuquila Basin, Jalisco, Mexico. Overall model prediction accuracy evaluated by AUC = 66%.

The number of livestock observed in each *ejido* correlated positively with the amount of TDF regrowth and TDF clearance (Fig 5), although its contribution to the log-likelihood value is less important than the number of fence posts (Table 4). There are around 6 *ejidos* that have large amounts of TDF change (points that deviate strongly from the regression line), as well as high levels of both livestock and fuelwood loads (Fig. 5a & 5b), which implies that these communities have a greater demand for forest resources and forest land. The observed positive association between TDF change and livestock suggests that the number of livestock is a good indicator of the intensity of use of the forest resources and might be a proxy that could be used in monitoring forest degradation in this type of socio-ecological landscape.

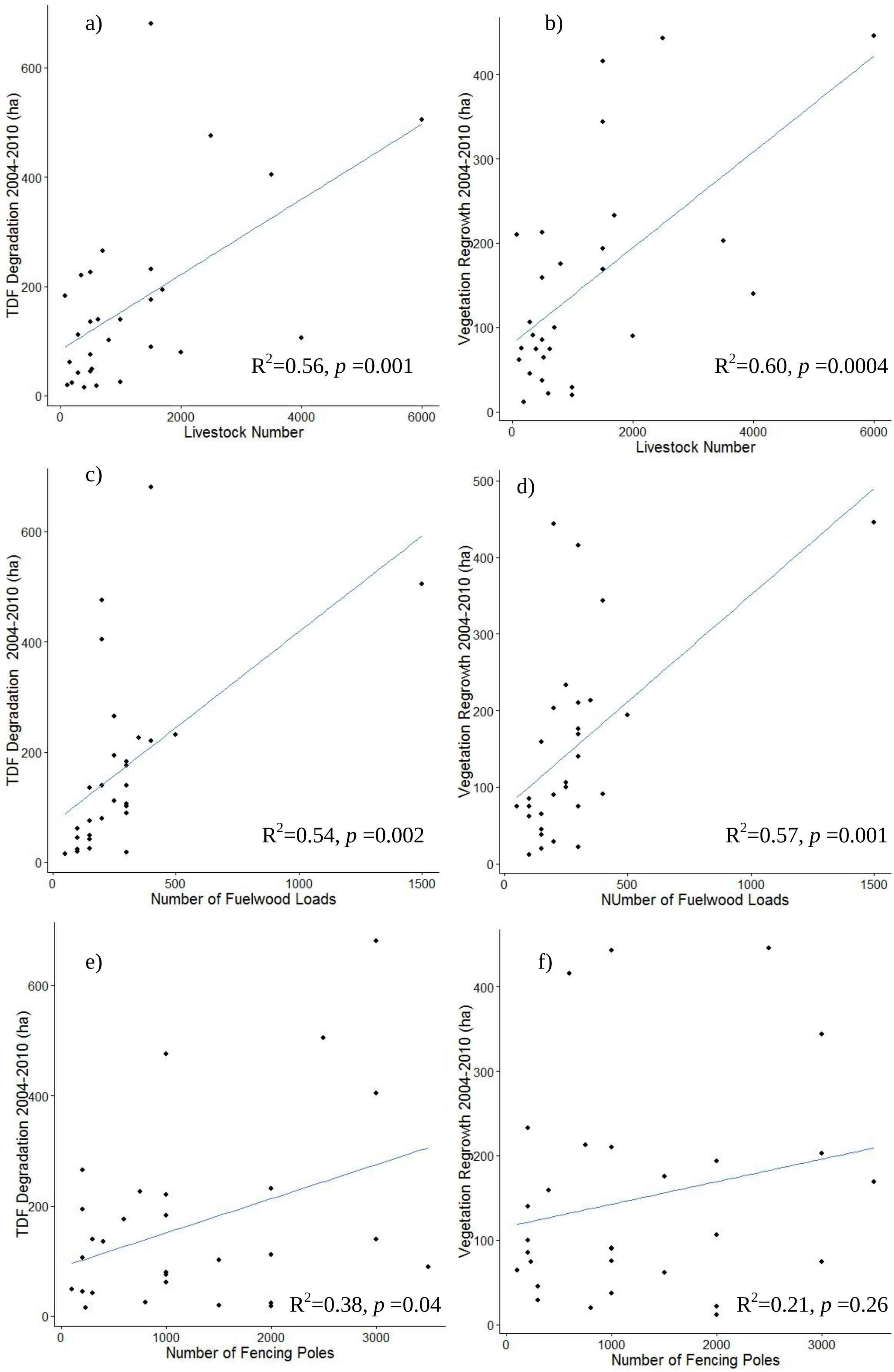

Figure. 5. Correlations between the resources used and the amount of TDF cover

change for 29 ejidos in the Ayuquila Basin, Jalisco, Mexico: a) number of livestock versus forest clearance; b) number of livestock versus forest regrowth; c) number of fuelwood loads extracted per year versus forest clearance; d) number of fuelwood loads harvested per year versus forest regrowth; e) number of fence posts harvested per year versus clearance; f) number of fence posts harvested per year versus regrowth (* $p<0.05$, $df = 27$).

4. Discussion

4.1. Monitoring and detection of forest degradation in shifting cultivation landscapes

In this study we characterized changes in TDF cover, showing that they can be statistically associated with forest degradation caused by the practice of shifting cultivation. The fact that there were similar amounts of forest regrowth and clearance over a 6-year period, both at the community and landscape levels, suggests that these landscapes under shifting cultivation are essentially sustainable, at least in terms of forest cover area and thus levels of above-ground carbon stock that can be associated with forest cover. This implies that presumably carbon emissions from forest clearance were offset by forest regrowth, however further work is clearly needed to test this; since carbon balance on shifting cultivation systems will depend on multiple factors. For instance, management practices such as the use of fire for clearing, and other ecological factors like the carbon sequestration capacity of forest regrowth; will play a role in determining carbon emissions. Several authors have reported rapid accumulation rates of above-ground biomass (AGB) during TDF regrowth after complete clearance (Lawrence *et al.*, 2005; Álvarez-Yépiz *et al.*, 2008; Lebrija-Trejos *et al.*, 2008); and age of land abandonment has been found to explain up to 46% of the variation in AGB for TDF (Becknell & Powers, 2014). Recent studies indicate, furthermore, that shifting cultivation can conserve and even increase carbon stocks in the soil (Salinas-Melgoza *et al.*, 2015). On the other hand, in terms of their structure and composition of species (and also probably functional traits), secondary TDFs formed after clearance are very different from their old-growth counterparts (Chazdon *et al.*, 2007) with a much lower average biomass density (Marín-Spiotta *et al.*, 2008; Kauffman *et al.*, 2009). In this sense they can be considered degraded, although their delivery of ecosystem services and value as habitat for biodiversity is still higher than many other land cover types.

We have provided evidence that shifting cultivation, as practiced within the *ejidos*, contributes to forest degradation but not to a net loss of forest cover. In our study area, shifting cultivation systems represent a form of local equilibrium, with a balance in rates of forest degradation (clearance) and recovery at the landscape scale, and as a result the potential for no net carbon emissions being produced in the long-term (Houghton, 2012). However, this situation could easily change if management practices within the *ejido*, government policies or markets favor an intensification of the agricultural practices, causing a shortening of the fallow periods or the cultivation of cash crops as has occurred in other areas (Dalle *et al.*, 2011; van Vliet *et al.*, 2012).

The methodology of the present study, a combination of high resolution image segmentation and a robust classification method (Rodriguez-Galiano *et al.*, 2012) based on spectral-textural information from the image, was successful in detecting small patches under shifting cultivation and enabling quantification of both the clearance and regrowth transitions of TDF subject to shifting cultivation management. As such, we suggest it might be a valuable tool for more widespread use to quantify forest degradation. Nevertheless, we recognize that using forest area cover change as a proxy of forest degradation could lead to underestimation, because further reductions in tree density can happen within the forest area, as has been found in arid and semi-arid ecosystems (le Polain de Waroux & Lambin, 2012). To improve the analysis, a classification of the canopy cover density could be integrated with the forest cover change analysis, however this will require even higher resolution data (~1 m) and the development of algorithms that can count tree crowns for TDF, which can be challenging due to seasonal leaf phenology and variability of forest structure (Arroyo-Mora *et al.*, 2005). Another adequate approach that might improve the detection of dynamics of shifting cultivation in TDF and its link to forest degradation, could be the use of multiple date time series of medium resolution images. Further research that compare the results of analyzing multiple dates of medium resolution and analyzing only two dates of high resolution image data should be attempt, in order to provide guidance on monitoring methods that might be more adequate for TDF.

The difficulties of detecting forest degradation that occurs under the canopy, such as overgrazing, excessive fuelwood collection and small-scale selective harvesting for timber, with satellite data have been widely acknowledged (GOFC-GOLD, 2013). We tried to overcome this limitation by associating the effect of these factors with the cycles of clearance and regrowth within a shifting cultivation landscape. These activities are possibly occurring in those parts of the TDF that showed no change in forest cover (65%), therefore part of this area could be considered low degradation. It is possible that the estimate of degradation that our method produces is not well correlated with these below-canopy impacts. Ideally, measurements of the amount of biomass actually extracted should be made. Though challenging, further research should be undertaken to investigate on-the-ground data of spatial variation in rates of grazing and wood extraction (ideally at a pixel level) with satellite data, to find out whether the latter detects the impact on forest structure and composition of the former (Romero-Duque *et* *al.*, 2007; Chaturvedi *et al.*, 2012). This is especially important in the context of REDD+, since avoiding degradation should not prohibit the use of forest resources but rather encourage change towards sustainable use.

The landscape-scale forest cover dynamics observed in the present study might have important implications for national and international forest environmental policy. In Mexico, there is a financial incentive for farmers to continue to clear regenerating forest from previously cultivated land because of the rules of the subsidy Program of Direct Payments to the Countryside (PROCAMPO), which makes payments per hectare of agricultural land. If the fallows are left uncut and advanced secondary forest develops, the government will classify it as abandoned land that is no longer used for agriculture and therefore the *ejidatarios* will lose their subsidies from PROCAMPO. Moreover, according to the modification of the legal Mexican Forest Code, once the land is designated as forest (when it is an advanced regenerated state), any tree harvesting in such areas will require a management plan (Román-Dañobeytia *et al.*, 2014). However, in addition to that, leaving the fallow to recuperate for long periods is not favored by farmers for logistical/labor reasons. As several farmers mentioned during our field interviews: "We need to clear the area because it grows too fast, in two-three years it is too tall, and then we cannot clear it". However, more detailed socio-economic and policy-oriented research is required to determine the effects of current forest and agricultural policies on the shifting cultivation cycles observed in complex TDF landscapes, such as those of the current study, and how they will affect the sustainability of shifting cultivation systems.

4.2 Drivers of forest degradation in tropical dry forest

We examined the importance of different biophysical and socio-economic variables to explain change in forest cover, which itself can be used as a proxy for forest degradation in a mosaic landscapes with shifting cultivation. Amongst the tested biophysical variables, slope was most closely related to forest degradation. Flatter areas had a higher probability of being used for shifting cultivation, but this is slightly influenced by elevation, such that there is a higher probability of degradation in flat areas on hilltops. Several studies have reported greater forest clearance on areas with less steep slopes (e.g. Newton & Echeverria, 2014), which can be attributed to better soil quality and less investment in labor than for steep slopes, where indeed most of the remaining unconverted TDF is found (Becknell *et al.*, 2012). This might have implications for management decisions related to land use planning that aim to enhance carbon stocks and avoid forest degradation in the landscape, because better environmental conditions that might increase net carbon sequestration of the landscape will be found on less steep terrain.

With reference to the tested socio-economic variables, as with all explanatory models, care needs to be taken not to confuse correlation with cause. The modeling results demonstrated that areas with a higher degree of marginalization had a higher probability of forest degradation. The marginalization index, which is a standard tool used to guide social policy in Mexico, is built on eight variables related to economic factors and education level of the entire population living in an *ejido* (CONAPO, 2012). Our findings suggest that *ejidos* characterized by lower incomes and low education levels, as well as less available TDF per person (those with higher population densities), are more dependent on clearing land for shifting cultivation. However, the causal order here needs to be considered carefully. Are communities carrying out shifting cultivation because they are marginalized (poor) and depend on it for subsistence, or are they poor because they are carrying out shifting cultivation? This question cannot be answered from our data but is important for the development of policy. In order for *ejidos* to participate in carbon mitigation projects the opportunities and constraints of each community should be carefully evaluated, so that poorer communities can also benefit from projects (Tschakert *et al.*, 2006). Furthermore, as discussed by Borrego & Skutsch (2014), there are marked differences within an *ejido* population in the proportion of income obtained from shifting cultivation and benefits derived from the TDF, by larger and by smaller operators.

Individual tests found evidence of significant positive correlation between the number of livestock or of fuelwood loads or (less strongly) fence posts and TDF cover change per *ejido*. Again, the relationship between number of cattle and fence post extraction with area dedicated to shifting cultivation should not necessarily be seen as causal since these could also be by-products (effects) of other processes. Moreover, the model selection procedure for probability of TDF cover change per sample pixel showed that these variables only had a weak relationship (and because of its high correlation with the number of livestock, fuelwood was not included as a separate explaining variable). It is possible that the effect of these variables is confounded with other variables included in the model, especially those related to socio-economic characteristics that distinguish the *ejidos*. In this area, livestock are used as a liquid asset that can be converted in an emergency; owning cattle requires capital and therefore only higher-income *ejidatarios* will be able to own several animals (Borrego & Skutsch, 2014), and the proportion of community members in this group are reflected in the marginalization indexes evaluated.

Statistical models are useful to determine the relative importance and interaction of possible agents of forest degradation, especially because it is feasible to incorporate many context-specific data, in this case information on livestock, harvested forest products, the ratio between TDF area and local population size etc. (Roy Chowdhury, 2006). However, there are many factors that interact and which together have an influence on the socio-ecological systems shaping the use of TDF resources. As with any model, the initial set of factors to be included will determine the outcome. For this reason, it is crucial that the context in which forest degradation is taking place is well understood on the ground (Mon *et al.*, 2012). For Mexico, future assessment of drivers of forest degradation and appropriate interventions to address it should include information on the different types of payment for ecosystem services and on other major market and subsidy incentives influencing decisions by land users, as well as factors influencing rural population density, e.g. through migration, that might be important in certain areas.

In Mexico REDD+ interventions promoting maintenance or enhancement of carbon stocks will probably be directed to *ejido*s, and there will therefore be a need for monitoring protocols that can effectively evaluate local interventions (Danielsen *et al.*, 2011; Mertz *et al.*, 2012) and that do not themselves impose major costs (Morales-Barquero *et al.*, 2014). The approach of collecting field data through interviews in combination with analysis of remotely sensed data, as tested in the present study, can be used to support the evaluation of REDD+ or other policy interventions. At a regional level keeping records of activities related to agriculture that drive forest degradation, such as the density of livestock, human populations and the size of agricultural parcels, is easier and less costly than obtaining precise estimates of AGB. It is important that if monitoring of land use activities is used instead of, or complementary to, AGB measurements, that such an analysis include both biophysical and socioeconomic data. This is important as these two types of information contributed almost equally to the explanation of spatial variation in the occurrence of forest degradation, in our study.

4.3 Shifting cultivation in the context of REDD+

Views on the sustainability of shifting cultivation are contested (Sunderlin *et al.*, 2008; Mertz *et al.*, 2012; Fox *et al.*, 2013) and this debate needs to be revisited in the context of REDD+ and the opportunities for climate change mitigation offered by modification of shifting cultivation practices acknowledged. Traditionally, shifting cultivators have been blamed for deforestation and there is a negative view towards this type of agriculture that argues in favor of land allocation to more intense agricultural systems in order to spare other land for conservation (Chandler *et al.*, 2013). However, secondary forests that derive from fallow systems recover carbon stocks and foster natural regeneration of some commercial TDF species (Valdez-Hernández *et al.*, 2014). Moreover shifting cultivation is the source of livelihoods for many smallholder farmers and represents the primary source of food security for many rural households (Padoch & Pinedo-Vasquez, 2010; Fox *et al.*, 2013). Therefore, in many circumstances prohibiting shifting cultivation and promoting a transition to a combination of intensified permanent agriculture systems and set-aside protected forest land is not socially nor environmental desirable (van Vliet *et al.*, 2012).

To maintain or enhance the sustainability of these systems, REDD+ interventions should target areas with higher potential for carbon sequestration for protection or, where necessary, active restoration (Hardwick *et al.*, 2004). Promoting longer fallow periods may be valuable to avoid the depletion of the carbon sequestration capacity of shifting cultivation systems (Lawrence *et al.*, 2010). The restriction of livestock browsing to certain areas within the shifting cultivation landscape would promote forest regrowth and carbon stock enhancement in other protected areas, though with a high risk of spillover leakage effects to other areas (Hett *et al.*, 2012). Incentives that seek to increase yield from shifting agricultural systems through improve management practices and new technologies without increasing carbon emissions (e.g. climate smart agriculture) should also be part of REDD+ interventions (Olander *et al.*, 2012), as has been demonstrated in the case of coffee agroforestry systems by Noponen *et al.*(2013). If, as a result, *ejidatarios* are able to produce enough maize for their own consumption and to feed their cattle on a smaller area of cultivated land, it is likely that a greater land area within the *ejido* can be allocated to carbon sequestration and fallow periods will be longer. This change could be incentivized, for example, by credit programs and subsidized fertilizers and seeds, and promoted through agricultural extension programs (Angelsen & Rudel, 2013).

Although there are options by which shifting cultivation can contribute to climate change mitigation, designing REDD+ payments to include shifting cultivation schemes poses multiple challenges. First, the consideration of shifting cultivation as a contributor to forest degradation will depend on the definition of forest that is applied in each country (Houghton, 2012), and on the time period at which the baseline is set. Second, designing payment systems for REDD+ to compensate for avoiding degradation by removing shifting cultivation is likely to run into problems in fulfilling the criterion of equity; unless they are well designed they risk removing the source of food security and livelihood of the most vulnerable community members without adequate compensation, especially in highly marginalized *ejidos*. Third, the impacts on the overall carbon budget of applying alternative agriculture management practices needs to be better understood, as well as the effects of such practices on local livelihoods, because so far there is little empirical evidence of effects of alternative management practices (Palm *et al.*, 2010). Fourth, including shifting cultivation in REDD+ interventions will require cross-sectoral coordination. For instance Mexico already has in place a system that subsidizes agriculture (PROCAMPO) and a payment for ecosystem services program. Both have potential for use in REDD+, but this will mean a joint work plan from institutions involved in the agriculture and the forestry sector. Despite these challenges, shifting cultivation has the potential to provide a good synergy between carbon, biodiversity and food security, if policies are well designed and take into consideration the above mentioned factors among other issues.

5. Conclusions

This study illustrates the value of integrating socio-economic and biophysical information to model potential drivers and correlates of forest degradation. Human decisions on how to use forest resources shape TDF landscapes, and form patterns that can be linked to specific activities. The assessment of patterns of forest change with high resolution satellite imagery allowed determination of the dynamics of small-scale agriculture in the area, and revealed that, over the time period studied, clearance and regrowth of TDF was balanced; indicating that possibly no net emissions were produced. Further work to test the impact of shifting cultivation systems on carbon stocks and carbon stock change in TDF, and to evaluate its long-term sustainability particularly in relation with carbon emissions, is clearly needed.

The approach of collecting field data through interviews and combining these with spatial analysis of remotely sensed data at the appropriate scale can be used to develop monitoring protocols aimed at evaluating REDD+ or other policy interventions at a landscape level. By identifying the activities that are linked to forest degradation, easyto-measure indicators can be developed. Once the appropriate scale of analysis has been identified, this approach can be extended to other areas of TDF with a mosaic landscape structure dominated by cyclical patchy forms of land use (e.g. many African woodlands, (Lambin, 1999)) and similar types of degradation process (e.g. selective logging or fuelwood collection). The integration of socio-economic and biophysical variables, as carried out in the present study, is essential to understand the impact of the use of the land and forest resources of TDF landscapes. Finally, socio-ecological landscapes such as TDF dominated by shifting cultivation are complex to analyze and there are still important knowledge gaps as regard to their dynamics. These interesting socio-ecological systems will continue to be a challenge for carbon mitigation policies for some time.

6.Acknowledgements

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7.References

Álvarez-Yépiz JC, Martínez-Yrízar A, Búrquez A, Lindquist C (2008) Variation in vegetation structure and soil properties related to land use history of old-growth and secondary tropical dry forests in northwestern Mexico. *Forest Ecology and Management*, **256**, 355–366.

Angelsen A, Rudel T (2013) Designing and implementing effective REDD+ policies: A forest transition approach. *Review of Environmental Economics and Policy*, **7**, 91–113.

Arroyo-Mora JP, Sanchez-Azofeifa GA, Kalacska M, Rivard B, Calvo-Alvarado JC, Janzen DH (2005) Secondary forest detection in a neotropical dry forest landscape using Landsat 7. *Biotropica*, **37**, 497–507.

Asner GP, Knapp DE, Broadbent EN, Oliveira PJC, Keller M, Silva JN (2005) Selective logging in the Brazilian Amazon. *Science (New York, N.Y.)*, **310**, 480–2.

Becknell JM, Powers JS (2014) Stand age and soils as drivers of plant functional traits and aboveground biomass in secondary tropical dry forest. *Canadian Journal of Forest Research*, **44**, 604–613.

Becknell JM, Kissing Kucek L, Powers JS (2012) Aboveground biomass in mature and secondary seasonally dry tropical forests: A literature review and global synthesis. *Forest Ecology and Management*, **276**, 88–95.

Blackie R, Baldauf C, Gautier D et al. (2014) *Tropical dry forests: The state of global knowledge and recommendations*. CIFOR, Bogor, Indonesia.

Bonilla-Moheno M, Redo DJ, Aide TM, Clark ML, Grau HR (2013) Vegetation change and land tenure in Mexico: A country-wide analysis. *Land Use Policy*, **30**, 355–364.

Borrego A, Skutsch M (2014) Estimating the opportunity costs of activities that cause degradation in tropical dry forest: Implications for REDD+. *Ecological Economics*, **101**, 1–9.

Bray DB, Antinori C, Torres-Rojo JM (2006) The Mexican model of community forest management: The role of agrarian policy, forest policy and entrepreneurial organization. *Forest Policy and Economics*, **8**, 470–484.

Chandler RB, King DI, Raudales R, Trubey R, Chandler C, Chávez VJA (2013) A small-scale land-sparing approach to conserving biological diversity in tropical agricultural landscapes. *Conservation biology : the journal of the Society for Conservation Biology*, **27**, 785–95.

Chaturvedi RK, Raghubanshi AS, Singh JS (2012) Effect of grazing and harvesting on diversity, recruitment and carbon accumulation of juvenile trees in tropical dry forests. *Forest Ecology and Management*, **284**, 152–162.

Chazdon RL, Letcher SG, van Breugel M, Martínez-Ramos M, Bongers F, Finegan B (2007) Rates of change in tree communities of secondary Neotropical forests following major disturbances. *Philosophical transactions of the Royal Society of London. Series B, Biological sciences*, **362**, 273–289.

CONAPO (2012) *Indices de marginalizacion 2010. National Population Council.* Mexico.

Crk T, Uriarte M, Corsi F, Flynn D (2009) Forest recovery in a tropical landscape: what is the relative importance of biophysical, socioeconomic, and landscape variables? *Landscape Ecology*, **24**, 629–642.

Cuevas R, Nuñez NM, F G, M S (1998) El bosque tropical caudcifolio en la Reserva de la Biosfera Sierra Manantlan, Jalisco-Colima, Mexico. *Boletin Instituto de Botanica Universidad de Guadalajara*, **5**, 445–491.

Dalle SP, Pulido MT, De Blois S (2011) Balancing shifting cultivation and forest conservation: Lessons from a “sustainable landscape” in southeastern Mexico. *Ecological Applications*, **21**, 1557–1572.

Danielsen F, Skutsch M, Burgess ND et al. (2011) At the heart of REDD+: a role for local people in monitoring forests? *Conservation Letters*, **4**, 158–167.

Dormann CF (2007) Assessing the validity of autologistic regression. *Ecological Modelling*, **207**, 234–242.

Eckert S, Engesser M (2013) Assessing vegetation cover and biomass in restored erosion areas in Iceland using SPOT satellite data. *Applied Geography*, **40**, 179–190.

Estrada M (2010) Mexico. In: *REDD , forest governance and rural livelihoods The emerging agenda*, pp. 95–109.

Fox J, Castella J-C, Ziegler AD (2013) Swidden, rubber and carbon: Can REDD+ work for people and the environment in Montane Mainland Southeast Asia? *Global Environmental Change*.

Gallardo-Cruz JA, Meave JA, González EJ et al. (2012) Predicting tropical dry forest successional attributes from space: is the key hidden in image texture? *PLoS one*, **7**, e30506.

Geist HJ, Lambin EF (2002) Proximate Causes and Underlying Driving Forces of Tropical Deforestation. *BioScience*, **52**, 143.

Gellrich M, Baur P, Koch B, Zimmermann NE (2007) Agricultural land abandonment and natural forest re-growth in the Swiss mountains: A spatially explicit economic analysis. *Agriculture, Ecosystems & Environment*, **118**, 93–108.

Gentry AH (1995) *Seasonally Dry Tropical Forests* (eds Bullock SH, Mooney HA, Medina E). Cambridge University Press, Cambridge.

Geoghegan J, Schneider L, Vance C (2004) Temporal dynamics and spatial scales : Modeling deforestation in the southern Yucatan peninsular region. *GeoJournal*, **61**, 353–363.

Getahun K, Van Rompaey A, Van Turnhout P, Poesen J (2013) Factors controlling patterns of deforestation in moist evergreen Afromontane forests of Southwest Ethiopia. *Forest Ecology and Management*, **304**, 171–181.

GOFC-GOLD (2013) *A sourcebook of methods and procedures for monitoring and reporting anthropogenic greenhouse gas emissions and removals associated with deforestation, gains and losses of carbon stocks in forests remaining forests, and forestation. Report version COP19-2*,. Wageningen,The Netherlands.

Haralick R, Shanmugan K, Dinstein I (1973) Textural features for image classification. *IEEE Transactions on Systems, Man and Cybernetics*, **3**, 610–621.

Hardwick K, Healey JR, Elliott S, Blakesley D (2004) Research needs for restoring seasonal tropical forests in Thailand: accelerated natural regeneration. *New Forests*, **27**, 285–302.

Hett C, Castella J-C, Heinimann A, Messerli P, Pfund J-L (2012) A landscape mosaics approach for characterizing swidden systems from a REDD+ perspective. *Applied Geography*, **32**, 608–618.

Horning N (2012) *Training Guide for Using Random Forests to Classify Satellite Images - v8. American Museum of Natural History, Center for Biodiversity and Conservation. Available from http://biodiversityinformatics.amnh.org/. (accessed on the date).*

Hosonuma N, Herold M, De Sy V et al. (2012) An assessment of deforestation and forest degradation drivers in developing countries. *Environmental Research Letters*, **7**, 044009.

Houghton RA (2012) Carbon emissions and the drivers of deforestation and forest degradation in the tropics. *Current Opinion in Environmental Sustainability*, **4**, 597–603.

Huete A (1988) A soil-adjusted vegetation index (SAVI). *Remote Sensing of Environment*, **25**, 295–309.

Hurni K, Hett C, Epprecht M, Messerli P, Heinimann A (2013) A Texture-Based Land Cover Classification for the Delineation of a Shifting Cultivation Landscape in the Lao PDR Using Landscape Metrics. *Remote Sensing*, **5**, 3377–3396.

INEGI (2000) XII Censo General de Población y Vivienda. 2000. Instituto Nacional de Estadística y Geografía. Aguascalientes, México.

INEGI (2010a) XIII Censo General de Población y Vivienda. 2010. Instituto Nacional de Estadística y Geografía. Aguascalientes, México.

INEGI (2010b) Conjunto Nacional de Uso del Suelo y Vegetación a escala 1:250,000, Serie IV; DGG-INEGI.

Kalacska M, Sanchez-Azofeifa GA, Rivard B, Calvo-Alvarado JC, Quesada M (2008) Baseline assessment for environmental services payments from satellite imagery: a case study from Costa Rica and Mexico. *Journal of environmental management*, **88**, 348–59.

Kauffman JB, Hughes RF, Heider C (2009) Carbon pool and biomass dynamics associated with deforestation , land use , and agricultural abandonment in the neotropics. *Ecological Applications*, **19**, 1211–1222.

Kissinger G, Herold M, De Sy V et al. (2012) Drivers of Deforestation and forest Degradation: A Synthesis Report for REDD+ Policymakers.

Lambin EF (1999) Monitoring forest degradation in tropical regions by remote sensing: some methodological issues. *Global Ecology and Biogeography*, **8**, 191–198.

Lawrence D, Suma V, Mogea JP (2005) Change in species composition with repeated shifting cultivation: limited role of soil nutrients. *Ecological Applications*, **15**, 1952–1967.

Lawrence D, Radel C, Tully K, Schmook B, Schneider L (2010) Untangling a Decline in Tropical Forest Resilience : Constraints on the Sustainability of. *Biotropica*, **42**, 21–30.

Lebrija-Trejos E, Bongers F, Pérez-García EA, Meave JA (2008) Successional change and resilience of a very dry tropical deciduousforest following shifting agriculture. *Biotropica*, **40**, 422–431.

Li P, Feng Z, Jiang L, Liao C, Zhang J (2014) A Review of Swidden Agriculture in Southeast Asia. *Remote Sensing*, **6**, 1654–1683.

Liaw A, Wiener M (2002) Classification and regression by randomForest. *R News*, **2**, 18–22.

Maass J, Balvanera P (2005) Ecosystem services of tropical dry forests: insights from long-term ecological and social research on the Pacific Coast of Mexico. *Ecology and …*, **10**.

Marín-Spiotta E, Cusack D, Ostertag R, Silver WL (2008) Trends in above and belowground carbon with forest regrowth after agricultural abandonment in the neotropics. In: *Post-Agricultural Succesion in the Neotropics* (ed Myster R), pp. 22–72. Springer, New York.

Mellor A, Haywood A, Stone C, Jones S (2013) The Performance of Random Forests in an Operational Setting for Large Area Sclerophyll Forest Classification. *Remote Sensing*, **5**, 2838–2856.

Menard S (2010) *Logistic Regression: From Introductory to Advanced Concepts and Applications*. SAGE Publications, 377 pp.

Mertz O (2009) Trends in shifting cultivation and the REDD mechanism. *Current Opinion in Environmental Sustainability*, **1**, 156–160.

Mertz O, Müller D, Sikor T et al. (2012) The forgotten D: challenges of addressing forest degradation in complex mosaic landscapes under REDD+. *Geografisk Tidsskrift-Danish Journal of Geography*, **112**, 63–76.

Miles L, Newton AC, DeFries RS et al. (2006) A global overview of the conservation status of tropical dry forests. *Journal of Biogeography*, **33**, 491–505.

Mon MS, Mizoue N, Htun NZ, Kajisa T, Yoshida S (2012) Factors affecting deforestation and forest degradation in selectively logged production forest: A case study in Myanmar. *Forest Ecology and Management*, **267**, 190–198.

Morales-Barquero L, Skutsch M, Jardel-Peláez E, Ghilardi A, Kleinn C, Healey J (2014) Operationalizing the definition of forest degradation for REDD+, with application to Mexico. *Forests*, **5**, 1653–1681.

Murdiyarso D, Skutsch M, Guariguata M, Kanninen M, Luttrell C, Verweij P, Stella O (2007) How do we measure and monitor forest degradation ? In: *Moving Ahead with REDD*, pp. 99–155. CIFOR.

Murphy PG, Lugo AE (1986) Ecology of tropical dry forests. *Annual Review of Ecology and Systematics*, **17**, 67–88.

Newton AC, Echeverria C (2014) Analysis of anthropogenic impacts on forest biodiversity as a contribution to empirical theory. In: *Forests and Global Change*, pp. 417–446.

Noponen MRA, Haggar JP, Edwards-Jones G, Healey JR (2013) Intensification of coffee systems can increase the effectiveness of REDD mechanisms. *Agricultural Systems*, **119**, 1–9.

Olander LP, Galik CS, Kissinger GA (2012) Operationalizing REDD+: scope of reduced emissions from deforestation and forest degradation. *Current Opinion in Environmental Sustainability*, **4**, 661–669.

Overmars KP, Verburg PH (2005) Analysis of land use drivers at the watershed and household level: Linking two paradigms at the Philippine forest fringe. *International Journal of Geographical Information Science*, **19**, 125–152.

Padoch C, Pinedo-Vasquez M (2010) Saving Slash-and-Burn to Save Biodiversity. *Biotropica*, **42**, 550–552.

Palm CA, Smukler SM, Sullivan CC, Mutuo PK, Nyadzi GI, Walsh MG (2010) Identifying potential synergies and trade-offs for meeting food security and climate change objectives in sub-Saharan Africa. *Proceedings of the National Academy of Sciences of the United States of America*, **107**, 19661–6.

Paradis E, Claude J, Stimmer K (2004) APE: analyses of phylogenetics and evolution in R language. *Bioinformatics*, **20**, 289–290.

Pebesma EJ (2004) Multivariable geostatistics in S: the gstat package. *Computers & Geosciences*, **30**, 683–691.

Pebesma EJ, Bivand RS (2005) Classes and methods for spatial data in R. *R News*, **5**.

Pelletier J, Ramankutty N, Potvin C (2011) Diagnosing the uncertainty and detectability of emission reductions for REDD + under current capabilities: an example for Panama. *Environmental Research Letters*, **6**, 024005.

Pelletier J, Codjia C, Potvin C (2012) Traditional shifting agriculture: tracking forest carbon stock and biodiversity through time in western Panama. *Global Change Biology*, **18**, 3581–3595.

Penman J, Gytarsky M, Krug T et al. (2003) *Definitions and Methodological Options to Inventory Emissions from Direct Human-induced Degradation of Forests and Devegetation of Other Vegetation Types*. Kanagawa.

Le Polain de Waroux Y, Lambin EF (2012) Monitoring degradation in arid andsemi-arid forests and woodlands: the case of the Argan woodlands (Morrocco). *Applied Geography*, **32**, 777–786.

Pontius RG, Schneider LC (2001) Land-cover change model validation by an ROC method for the Ipswich watershed, Massachusetts, USA. *Agriculture, Ecosystems & Environment*, **85**, 239–248.

Portillo-Quintero CA, Sánchez-Azofeifa GA (2010) Extent and conservation of tropical dry forests in the Americas. *Biological Conservation*, **143**, 144–155.

Putz FE, Redford KH (2010) The Importance of Defining “Forest”: Tropical Forest Degradation, Deforestation, Long-term Phase Shifts, and Further Transitions. *Biotropica*, **42**, 10–20.

Read L, Lawrence D (2003) Recovery of Biomass Following Shifting Cultivation in Dry Tropical Forests of the Yucatan. *Ecological Applications*, **13**, 85–97.

Rodriguez-Galiano VF, Ghimire B, Rogan J, Chica-Olmo M, Rigol-Sanchez JP (2012) An assessment of the effectiveness of a random forest classifier for land-cover classification. *ISPRS Journal of Photogrammetry and Remote Sensing*, **67**, 93–104.

Román-Dañobeytia F, Levy-Tacher S, Macario-Mendoza P, Zúñiga-Morales J (2014) Redefining Secondary Forests in the Mexican Forest Code: Implications for Management, Restoration, and Conservation. *Forests*, **5**, 978–991.

Romero-Duque LP, Jaramillo VJ, Pérez-Jiménez A (2007) Structure and diversity of secondary tropical dry forests in Mexico, differing in their prior land-use history. *Forest Ecology and Management*, **253**, 38–47.

Rouse JW, Haas RH, Schell JA, D.W. Deering D (1973) Monitoring vegetation systems in the Great Plains with ERTS. In: *Third ERTS Symposium, NASA SP-351 I*, pp. 309–317.

Roy Chowdhury R (2006) Landscape change in the Calakmul Biosphere Reserve, Mexico: Modeling the driving forces of smallholder deforestation in land parcels. *Applied Geography*, **26**, 129–152.

Rzedowski .I.J. (1978) *La vegetacion de Mexico*. Limusa, Mexico,D.F., 431 pp.

Saikia A (2014) *Over-Exploitation of Forests*. Springer International Publishing, Cham, 19-24 pp.

Salinas-Melgoza MA, Skutsch M, Lovett CJ (2015) Shifting cultivation in the context of REDD+: a case study of Mexican tropical dry forest. *Land Use Policy*, **submitted**.

Salvini G, Herold M, De Sy V, Kissinger G, Brockhaus M, Skutsch M (2014) How countries link REDD+ interventions to drivers in their readiness plans: implications for monitoring systems. *Environmental Research Letters*, **9**, 074004.

Sanchez-Azofeifa GA, Portillo-Quintero C (2011) Extent and Drivers of Change of Neotropical Dry Forests. In: *Seasonally Dry Tropical Forests* (eds Dirzo R, Young HS, Mooney HA, Ceballos G), pp. 45–59. Island Press, Washington, DC.

Sánchez-Azofeifa GA, Quesada M, Rodríguez JP et al. (2005) Research priorities for Neotropical dry forests. *Biotropica*, **37**, 477–485.

SEMARNAT (2010) *Visión de México sobre REDD+: hacia un estrategia nacional. Comisión Nacional Forestal.*

Skutsch M, Simon C, Velazquez A, Fernández JC (2013) Rights to carbon and payments for services rendered under REDD+: Options for the case of Mexico. *Global Environmental Change*, **23**, 813–825.

Souza CM, Roberts DA, Cochrane MA (2005) Combining spectral and spatial information to map canopy damage from selective logging and forest fires. *Remote Sensing of Environment*, **98**, 329–343.

Sunderlin W, Dewi S, Puntodewo A, Muller D, Angelsen A, Epprecht M (2008) Why forests are important for global poverty alleviation: a spatial explanation. *Ecology and Society*, **13**.

Trejo I, Dirzo R (2000) Deforestation of seasonally dry tropical forest a national and local analysis in Mexico. *Biological Conservation*, **94**, 133–142.

Tschakert P, Coomes OT, Potvin C (2006) Indigenous livelihoods , slash-and-burn agriculture , and carbon stocks in Eastern Panama. *Ecological Economics*, **60**, 807–820.

UNFCCC (2010) Outcome of the work of the ad hoc working group on long-term cooperative action under the convention—policy approaches and positive incentives on issues relating to reducing emissions from deforestation and forest degradation in developing countries: and .

Valdez-Hernández M, Sánchez O, Islebe GA, Snook LK, Negreros-Castillo P (2014) Recovery and early succession after experimental disturbance in a seasonally dry tropical forest in Mexico. *Forest Ecology and Management*, **334**, 331–343.

Vescovo L, Gianelle D (2008) Using the MIR bands in vegetation indices for the estimation of grassland biophysical parameters from satellite remote sensing in the Alps region of Trentino (Italy). *Advances in Space Research*, **41**, 1764–1772.

Van Vliet N, Mertz O, Heinimann A et al. (2012) Trends, drivers and impacts of changes in swidden cultivation in tropical forest-agriculture frontiers: A global assessment. *Global Environmental Change*, **22**, 418–429.

Table S1. Spot 5 image data used in the study.

Image Reference Name	**Row - Path**	**Date of acquisition**	**RMSE (pixels)**	**Number of Ground Control Points**
E55773100401311J2A00009	577-310	31.01.2004	0.66	45
E55783100401212J2A09009	578-310	21.01.2004	0.47	14
E55783110401212J2A05007	578-311	04.01.2004	0.42	13
E55793110403282J2A08002	579-311	28.03.2004	0.92	16
E55773101001282J2A06002	577-310	28.01.2010	0.86	13
E55783101002242J2A09017	578-310	24.02.2010	0.23	52
E55783111002242J2A06020	578-311	24.02.2010	0.19	31
E55793111011162J2A00035	579-311	11.16.2010	0.18	25

Table S2 . Vegetation indices used in the study.

Index	Algorithm	Reference
Homogeneity Index *	$\sum_{i,j=0}^{N-1} \frac{Pij}{1+(i-j)^2}$	Haralick *et al.*, (1973)
Canopy Index**	$\mathrm{CI} = \mathrm{SWIR} - \mathrm{G}$	Vescovo & Gianelle (2008)
Normalized Difference Vegetation Index**	$\mathrm{NDVI} = \frac{\mathrm{NIR} - \mathrm{R}}{\mathrm{NIR} + \mathrm{R}}$	Rouse *et al.* (1973)
Soil Adjusted Vegetation Index **	$\mathrm{SAVI} = \frac{\mathrm{NIR} - \mathrm{R}}{\mathrm{NIR} + \mathrm{R} + 0.5} * (1 + 0.5)$	Huete (1988)

* Is calculated based on the grey level co-occurrence matrix (GLCM), each element of the GLCM indicates the relationship between grey levels of pixels in specific directions or distances. *Pij* indicates the probability in that cell of finding the reference value *i* in combination with a neighbour pixel. *j*.
** G = green band (Spot 5 band 1), R = red band (Spot 5 band 2), NIR = near infrared band (Spot 5 band 3) and SWIR = short wave infrared (Spot 5 band 4).

Table S3 Pearson correlation coefficient values (r) for the numeric variables used in the statistical model for estimating probability of forest degradation in Ayuquila Basin, Jalisco, Mexico (Variable explanations and names are provided in Table 1) .

	Elevation	Fuelwood	Fence	Livestock	Dist	Slope	Ejidatarios	Pop:TDF	Parcel_ S	Road
Elevation	1.000	-0.207	-0.299	-0.249	0.119	0.356	-0.145	-0.070	-0.313	0.460
Fuelwood	-0.207	1.000	0.442	0.811	-0.351	-0.171	0.571	-0.231	0.635	-0.143
Fence	-0.299	0.442	1.000	0.399	-0.260	-0.031	0.580	-0.183	0.623	0.011
Livestock	-0.249	0.811	0.399	1.000	-0.309	-0.212	0.581	0.054	0.672	-0.169
Dist	0.119	-0.351	-0.260	-0.309	1.000	0.141	-0.523	0.113	-0.466	0.096
Slope	0.356	-0.171	-0.031	-0.212	0.141	1.000	-0.147	-0.076	-0.196	0.384
Ejidatarios	-0.145	0.571	0.580	0.581	-0.523	-0.14	1.00	-0.286	0.052	-0.135
Pop:TDF	-0.070	-0.231	-0.183	0.054	0.113	-0.076	-.286	1.000	-0.270	-0.099
Parcel _S	-0.313	0.635	0.623	0.672	-0.466	-0.196	0.052	-0.270	1.000	-0.194
Road	0.460	-0.143	0.011	-0.169	0.096	0.384	-0.135	-0.099	-0.194	1.000

Table S4. Area (ha) of tropical dry forest found in each community of the Ayuquila Basin, Jalisco, Mexico.

ID	Name	Area analyzed (ha)	Ejidatarios	Number of Households	Population	No land cover change (ha)	TDF cover lost (ha)	TDF cover gain (ha)	Net change in TDF cover (2004-2010, ha)
1	Agua Hedionda y Anexos	902	57	50	237	531.3	220.4	91.1	-129.2
2	Ahucapan	841	129	271	985	668.5	79.9	89.7	9.8
3	Ayuquila	456	60	230	862	341.6	49.0	64.4	15.4
4	Ayutita	614	40	98	334	390.9	139.7	74.7	-64.9
5	Chiquihuitlan y Agua Salada	3724	148	60	237	2507.4	681.5	343.6	-337.9
6	Coatlancillo	1558	45	159	565	1112.3	226.3	212.7	-13.6
7	El Ahucate	291	23	72	242	245.0	25.0	20.0	-5.0
8	El Chante	1074	240	524	1880	853.5	112.0	105.9	-6.2
9	El Jardin	577	45	40	175	435.8	61.2	75.3	14.1
10	El Limon	1360	450	961	3102	1099.0	89.0	169.0	80.0
11	El Palmar	322	90	15	234	286.5	23.7	11.3	-12.4
12	El Rodeo	1502	32	41	161	1174.7	101.9	175.8	73.9
13	El Temazcal	5403	81	33	116	4469.1	475.5	443.3	-32.1
14	La Laja	1591	50	114	454	1168.9	182.4	210.2	27.8
15	Lagunillas	808	98	242	836	694.4	74.9	37.2	-37.6
16	Las Pilas	456	47	94	387	325.4	45.0	85.0	40.0
17	Los Mezquites	1427	57	72	301	1109.0	135.0	159.0	24.0
18	Mezquitan	500	64	230	885	416.8	19.2	62.1	42.9
19	San Agustin	935	140	102	342	762.7	139.9	28.8	-111.2
20	San Antonio	1650	90	158	669	1211.5	194.4	233.2	38.8
21	San Buenaventura	1267	26	46	158	1178.0	14.7	74.3	59.7
22	San Clemente	1328	212	310	1182	960.2	264.7	99.6	-165.0
23	San Jose de las Burras	2494	150	134	541	1876.8	176.3	415.9	239.6

24	San Juan Jiquilpan	1144	130	455	1789	881.7	106.1	140.1	34.0
25	San Miguel	668	45	132	446	626.7	18.1	21.3	3.2
26	Tecomatlan	802	53	35	129	710.0	41.0	45.0	4.0
27	Tonaya	4826	282	955	3497	3823.4	505.1	446.1	-59.0
28	Tuxcacuesco	2051	165	405	1538	1380.0	404.0	203.0	-201.0
29	Zenzontla	2400	67	60	381	1943.0	231.0	194.0	-37.0
	Total	42971.0	3116	6098	22665	33184.2	4836.6	4331.6	-505.0

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Fig S1. Geographic representation of residuals for the probability model of forest degradation for the Ayuquila Basin, Jalisco, Mexico.

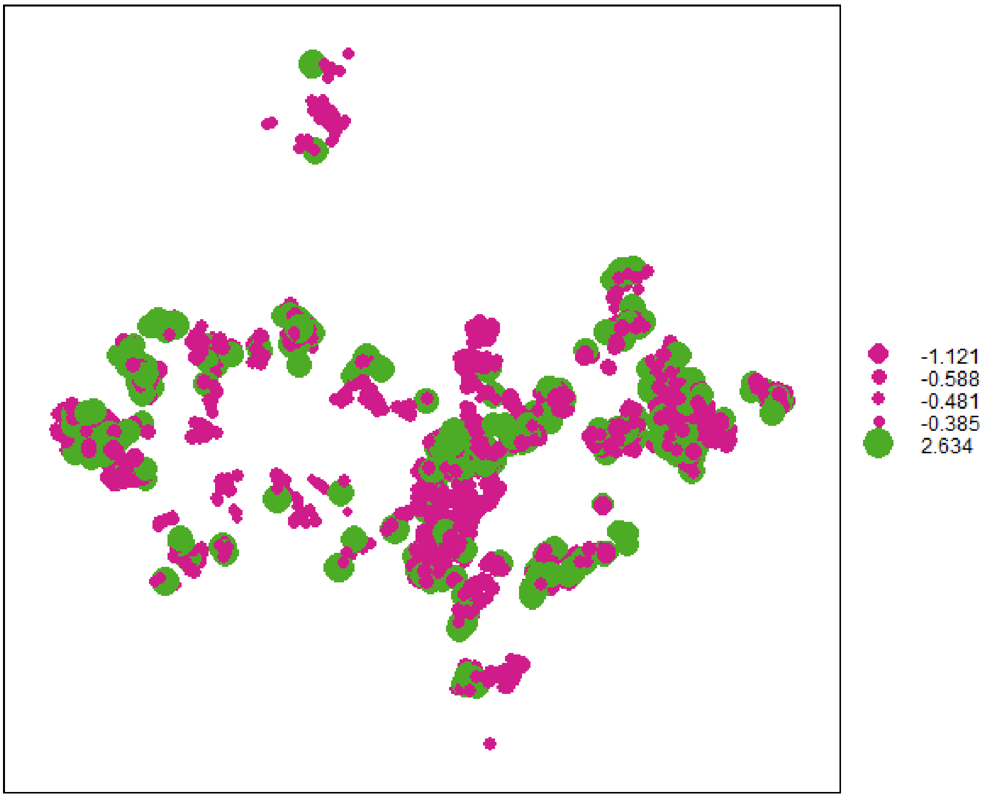

Fig S2. Semivariogram of residuals for the probability model of forest degradation for the Ayuquila Basin, Jalisco, Mexico